AD-A057 305 STANFORD UNIV CALIF DEPT OF ELECTRICAL ENGINEERING F/G 9/3

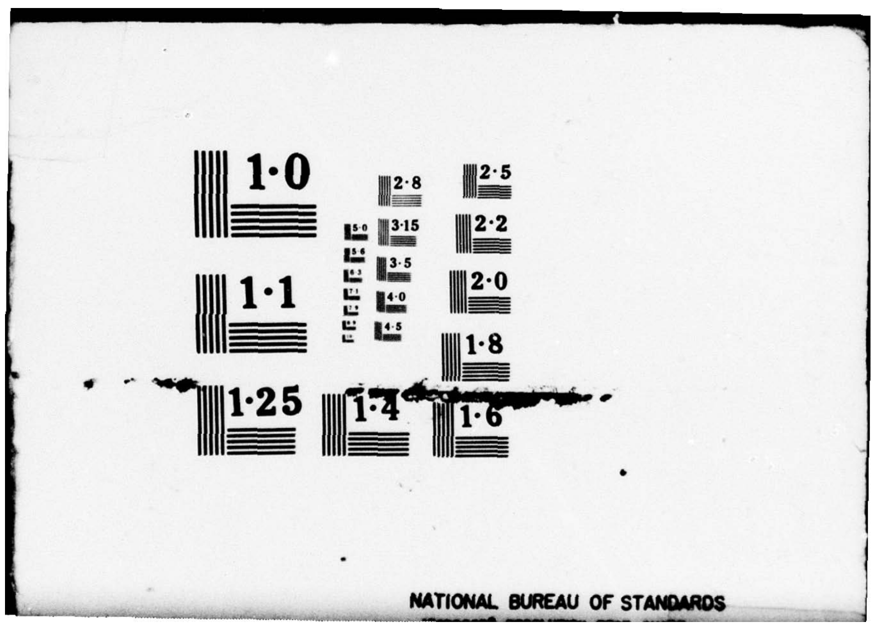
OPTIMAL DATA COMPRESSION ALGORITHMS.(U)

APR 78 R M GRAY, M E HELLMAN F44620-73-C-0065

UNCLASSIFIED AFOSR-TR-78-1179 NL

1 OF 1
ADA
057305

END
DATE
FILMED
9 -78
DDC


1·0
2·8
2·5
3·15
2·2
5·0
5·6
3·5
2·0
4·0
1·1
4·5
1·8
1·25
1·4
1·6
NATIONAL BUREAU OF STANDARDS

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

(19) REPORT DOCUMENTATION PAGE

READ INSTRUCTIONS BEFORE COMPLETING FORM

LEVEL II

1. REPORT NUMBER (18) AFOSR TR- 78-1179	2. GOVT ACCESSION NO.	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (and Subtitle) (6) OPTIMAL DATA COMPRESSION ALGORITHMS.		5. TYPE OF REPORT & PERIOD COVERED (9) Final rept. 1 May 73-30 Apr 78
		6. PERFORMING ORG. REPORT NUMBER
7. AUTHOR(s) (10) Robert M./Gray [redacted] Martin E./Hellman		8. CONTRACT OR GRANT NUMBER(s) (15) AFOSR F 44620-73-C-0065
9. PERFORMING ORGANIZATION NAME AND ADDRESS Stanford University Department of Electrical Engineering Stanford, California 94305		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS 61102F (16) 2304 A6 (17) A6
11. CONTROLLING OFFICE NAME AND ADDRESS Air Force Office of Scientific Research/NM Bolling AFB, Washington, DC 20332		12. REPORT DATE 1978 (11) 30 Apr 78
		13. NUMBER OF PAGES 20
14. MONITORING AGENCY NAME & ADDRESS (if different from Controlling Office)		15. SECURITY CLASS. (of this report) UNCLASSIFIED (12) 25p.
		15a. DECLASSIFICATION/DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)

Approved for public release; distribution unlimited

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

D D C
RECEIVED
AUG 10 1978
F

18. SUPPLEMENTARY NOTES

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

This research project on optimal compression algorithms was concerned with several problems in the area of digital communications and the elimination of redundancy. The importance of the problem arises from the growing use of digital transmission in the military as well as the civilian communications field. There are many advantages enjoyed by digital transmission, the most notable being that there is almost no signal to noise degradation when relayed through a number of repeaters, whereas analog → next page

DD FORM 1 JAN 73 1473 EDITION OF 1 NOV 65 IS OBSOLETE

UNCLASSIFIED

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

400 852

20. Abstract

repeaters lose 3 db every time the number of repeaters is doubled. The one marked disadvantage of digital transmissions is that digitization of a basically analog source such as speech or TV results in a bandwidth expansion using conventional techniques. Good quality digitized voice requires on the order of 50,000 bits per second if data compression is not used. With conventional techniques, this requires 30 kHz of bandwidth while the analog voice signal could be transmitted over a 3 kHz channel. The area of bandwidth compression seeks to remove this disadvantage by eliminating the redundancy in the signal. Over 30 papers and reports were published on this subject by the PI's during this period.

FINAL REPORT

AFOSR CONTRACT F-44620-73-C-0065

May 1, 1973 to April 30, 1978

Robert M. Gray
Martin E. Hellman

SECTION I

INTRODUCTION

Both military and civilian communication systems are becoming increasingly digital, as opposed to analog, in nature due to several factors:

1. Digital transmission can be made more noise-immune through the use of error correcting and detecting codes. This applies to both natural and malicious noise (e.g., jamming).
2. The cost of digital hardware has decreased markedly, and there is every indication the trend will continue.
3. Digital transmission suffers almost no signal-to-noise degradation when relayed through a number of repeaters. Analog repeaters lose 3 dB every time the number of repeaters is doubled. Thus, for example, eight repeaters cause a 9 dB loss in an analog system. On a digital system operating at a 10^{-5} bit error rate the corresponding loss is only 1 dB.
4. Digital transmission is much more amenable to protection by cryptographic techniques.

The one marked disadvantage of digital transmission is that digitization of a basically analog source such as speech or TV results in a bandwidth expansion using conventional techniques. Good quality digitized voice requires on the order of 50,000 bps if source coding is not used. With usual modulation techniques this requires a 25 to 50 kHz channel, whereas the analog voice signal could be transmitted over a 3 kHz channel.

For a given bandwidth allocation the digital system will thus be able to handle only about one-tenth the traffic that could be handled by an analog system.

Source coding (also known as bandwidth compression or data reduction) attempts to remove this disadvantage by reducing the required data rate. For example, source coding of voice with a ten-to-one compression factor would allow as many digital as analog channels. Source coding provides the additional advantage of reducing the signal energy required to transmit a block of data.

Although source coding holds promise for the use of digital transmission, cost is a major obstacle to its use. Source coders which achieve significant compression have been complex and therefore expensive. Another aspect of this complexity problem has further hindered the use of source coding in remote telemetry and other systems where operations performed at the transmitter are orders of magnitude more expensive than operations performed at the receiver. This has to do with the fact that, to date, the source encoder has borne the brunt of the overall system complexity, while the source decoder has been much simpler. This is in contrast with channel coding (coding for error correction) where the channel decoder must be complex, while the channel encoder can be simple. This partially explains why channel coding has found more widespread use than source coding. Besides remote telemetry (e.g., space, ocean, behind enemy lines), systems which have a large ratio of transmitters to receivers, or in which the transmitter is expendable, will have an asymmetric complexity cost, with the transmitter complexity having the higher cost. Examples of such systems are RPV's

and communication to a central command. We have developed several source coding techniques which are well matched to such applications. These techniques, as well as progress in related areas are covered in the next section.

SECTION II - A

CONVOLUTIONAL SOURCE ENCODING

Most source coding schemes utilize complex encoders and are thus not well matched to remote telemetry and other applications where the encoder must be simple, inexpensive and reliable. We have developed a convolutional source encoding technique which is well matched to such applications because the encoder is extremely simple. ["Convolutional Source Encoding", IEEE Trans. on Info. Theory, Nov. 1975.]

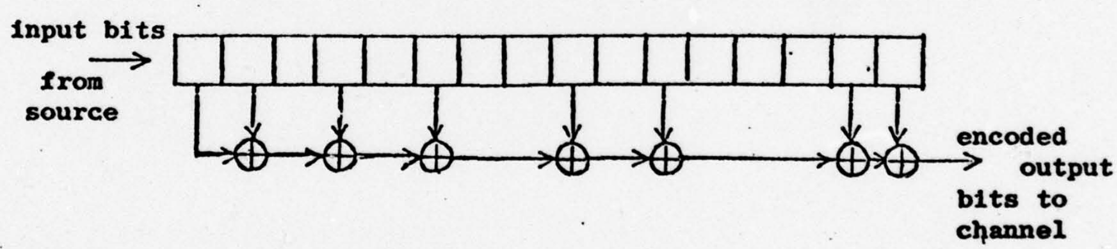
The decoder is much more complex, and effort was devoted to simplifying the decoder. A small simulation on video data indicates that compression ratios of 2:1 or more are possible without introducing *any* distortion into the reproduced data (noiseless coding).

The basic system utilizes a convolutional encoder and a sequential decoder. The encoder operates at rates greater than one, whereas convolutional coders used for channel coding operate at rates less than one.

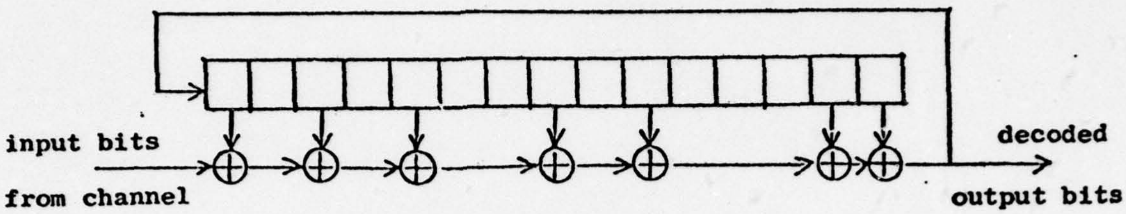
It is easiest to understand the operation of our convolutional source coding system by first understanding its operation when used for joint source and channel coding. In usual systems the data is encoded in two stages. First a source coder removes redundancy from the data to reduce the number of bits which must be communicated. Then a channel coder adds redundant bits in a controlled manner so that most errors which occur on the channel can be corrected. If source coding removes redundancy and channel coding adds it back in, one might try to dispense with both operations and use the natural redundancy of the source for error correction. A simple example shows why this cannot usually be

done. If the message "I AM NOT ABLE TO PROVIDE SUPPORT." is transmitted directly and a single character is received in error: "I AM NOW ABLE TO PROVIDE SUPPORT." is received. Not only is the error overlooked, but the meaning of the message has been reversed. This is in spite of the fact that the amount of redundancy is more than sufficient to correct single errors. Although the redundancy is large it is not evenly distributed.

We have developed a very simple device to transform the redundancy of the source into a usable form. This joint source and channel encoder is a rate one convolutional encoder. It consists of a shift register and a number of mod-2 adders (exclusive OR gates). A typical encoder is shown below:



This encoder has sixteen stages, and typically 25-100 stages will be more than adequate. The output bits are transmitted over the noisy channel and placed through the decoder which performs the inverse operation of the encoder. The decoder which corresponds to the above encoder is shown below.



It is seen that because of the feedback in the decoder, even a single transmission error will cause many errors in the decoded information. If there are enough stages in the encoder then the output following an error is complete gibberish. For example, the same single character error as in the message above causes the output: "I AM NOWJ.NXAAVWM,E WTYROVBGZ, RI". It is easily seen that the characters most likely to be in error are the W and the J of NOWJ... . A first attempt would be to change the J of NOWJ... to a blank, making the text "I AM NOW...". This puts two errors in the decoder, the first being due to the channel, the second being due to our attempted correction. Thus the output is again gibberish: "I AM NOW HU.CVKIWXRORBHUWTZHUIGK*". When we try correcting the W we find the output is meaningless except when the proper correction to a T is tried. This example used a 5 bit code with star = 00000, A = 00001, ... Z = 11010, blank = 11011, period = 11100, comma = 11101, quote = 11110, question mark = 11111. Low order bits are encoded first. This code has lower redundancy than most codes in common use (e.g., ASCII) and therefore we expect even greater correction capabilities with these other codes.

Note the simplicity of both the encoder and the feedback decoder, each consisting of a shift register and several exclusive OR gates. The

only complexity involved is in recognizing what is and what is not a meaningful message and in deciding which errors are most likely. It is the necessity of having such a capability which makes the receiver more complex than the transmitter. This requirement can be met by having a sequential decoder available at the receiver. The sequential decoder need not have a complete description of the source characteristics, but of course a less complete description doesn't allow as great an error correction capability.

The sequential decoder is similar to usual sequential decoders except that its metric has an added term which depends on the source statistics. For a discrete memoryless source with probability distribution $q(u)$ on its outputs, and a discrete memoryless channel with transition probabilities $p(y|x)$, the metric increment on a branch is

$$m = \ln \frac{p(y|x)}{p(y)} + \ln q(u) .$$

We have shown that so long as H, the entropy or rate of the source, is less than C, the capacity of the channel, reliable transmission is possible. That is, as the constraint length of the convolutional encoder ν tends to infinity the probability of a decoding error tends to zero. This one step, combined source and channel encoder is thus as good as the best two step, source and channel encoders.

If $H > C$ we must go to a lower rate convolutional code to obtain reliable transmission. If $H < 2C$ then a rate one-half code suffices; if $H < 1.5C$ then a rate two-thirds code suffices; etc.

Conversely, if $H < C$ it would seem there should be some margin for

using a higher rate code. In the extreme, with a noiseless channel there is no point in encoding the data with our rate one encoder since no error protection is needed. The question is how to generate information lossless convolutional codes with rates greater than one. Somewhat surprisingly, if $H < C/2$ then just throwing away every other output from our rate one encoder results in a rate two encoder which allows reliable decoding using the previously described metric. If $H < 2C/3$ then throwing away every third output from a rate one encoder works, or we can take a rate one-half encoder and throw away the 1st, 2nd, 4th, 5th, 7th, 8th, etc. set of outputs. Either technique yields a rate three-halves encoder. A little thought shows that these encoders are the obvious generalization of error correcting convolutional encoders to rates greater than one.

It is interesting to note that the encoder is universal (e.g., in the English language example the same encoder could be used to encode German). Only the decoder's metric depends on the source. Again this is well suited to applications in which encoder complexity must be low, since frequently the source statistics are not known *a priori* and a non-universal encoder would have to be programmable. With our system the first few messages (e.g. photographs of a planet) could be repeated to allow decoding without knowledge of the source statistics. The source statistics could be estimated and used on future messages which then need not be repeated.

Another universal approach is to compile statistics on the source while encoding its output. These statistics are transmitted at the end of the message and allow use of the optimal metric at the decoder. Because our encoder is universal, a 2:1 compression is possible using the

same encoder, no matter what the statistics of the source are, provided they allow a 2:1 compression (i.e., the source is at least 50% redundant). Because of the encoder's universality the source output need not be stored for encoding after the statistics are known. Rather, the compressive encoding proceeds <u>while</u> the statistics are compiled. Of course, the decoder must store the received data until the statistics are transmitted. But in applications where decoder complexity can be many times greater than encoder complexity (e.g., remote telemetry) this is no problem.

The proof that reliable decoding is possible uses arguments from the theory of branching processes. It does not treat the problem of computational effort and as one might expect there is a problem analogous to the existence of the computational cutoff rate for normal sequential decoding. Koshelev independently realized the applicability of convolutional codes to one step encoding and derived bounds on the expected number of computations. He shows that a source has a computational cutoff entropy H_{comp} which is larger than H and that the expected number of computations per bit is finite only when $H_{comp} < R_{comp}$.

We also investigated application of these techniques to real facsimile data. Knowing the behavior of the algorithm on such sources should allow easier extensions to other sources. We concentrated on facsimile for several reasons.

1. It is an important area for source coding. A high quality photo requires on the order of 10^7 bits for digital transmission before source coding. For satellites, space probes and photo reconnaisance where hundreds of photos are involved this represents a tremendous amount of information. Source coding has been used successfully in some instances, but simpler encoders would be cheaper and more reliable and

would therefore find more widespread use.

2. Solving the problem of source coding for facsimile is probably a necessary first step toward solving the problem of source coding for television. The video portion of television is just a sequence of related facsimile pictures.

3. By first dealing with black/white (no gray) facsimile we can simplify the problem and concentrate on the basic problem of source coding a binary source with memory.

A preliminary investigation brought several problems to light. The most pressing problem was to find a good metric for facsimile. Intuition and trial and error did not seem to be fruitful approaches. Analytical studies indicated how the metric should depend on the source statistics, and we compiled and used such statistics in the design of our metric.

Another problem studied concerned high detail areas of the picture which overload the computational abilities of the decoder, while low detail areas waste transmission time. We studied the use of a variable rate encoder in which the transmission-starved high detail areas can effectively borrow transmission time from the transmission-rich low detail areas. This approach was used in our facsimile simulation.

SECTION II - B

Tree and Trellis Codes

The basic Shannon-style source coding theorems relating the optimum achievable average distortion for a data compression system to the distortion-rate function were developed for time invariant trellis or tree coding systems and ergodic sources. Tree codes consist of a time-invariant possibly nonlinear filter (a sliding-block code) as decoder and a matched tree search algorithm such as the Viterbi algorithm which finds for a given source sequence a channel sequence which will drive the decoding filter so as to produce a good reproduction to the original sequence. These results removed the requirement of previous coding theorems for either time-varying decoders or infinite length decoders and hence better modeled practical data compression systems. The basic coding theorems were also extended to systems where the source is incorrectly or incompletely specified (universal coding). These results were published in [1,2].

The above mentioned results guarantee the existence of good tree coding data compression systems. As is often the case with the Shannon theory, however, the theorems are existence proofs and provide no indication of how to actually design a data compression system for a given source and distortion measure. It was shown in the above research, however, that the problem of designing a good decoder (which then specifies the encoder) is equivalent to designing a filter such that when driven by a memoryless discrete sequence it produces a good "fake" or simulation of the original source. This led to the development of

the fake process approach to the design of tree coding data compression systems. Roughly speaking, several intuitive techniques were used to produce good fakes of given source models by matching the marginal probabilities and the second order averages (autocorrelation). These systems were developed and simulated for Gaussian memoryless, autoregressive, and moving average processes with a mean-squared error fidelity criterion and one bit per symbol compression systems. These systems worked quite well providing, for example, an improvement of .7dB over Lloyd-Max optimal quantization for memoryless sources, 1 dB over predictive quantization on autoregressive sources, and over 5 dB over predictive quantization on moving average sources. This improvement was effectively half the distance between the traditional systems and the optimum achievable as given by the Shannon distortion-rate curve and it was obtained at the expense of only a moderate increase in complexity. This research is reported in detail in [3,4].

Speech Compression

Our initial work on speech compression was the adaption of the traditional theory of the asymptotic behavior of optimum quantizers and the Lloyd-Max algorithm for computing optimum quantizers to the problem of single-symbol quantization of the reflection coefficients arising in Linear Predictive Coded (LPC) speech compression systems. The principle novelty here was the use of the log spectral distortion measure popular in the speech community. This distortion measure is not of the usual form assumed in information theory and it required a new approach. We developed experimental rate vs. distortion curves for uniform

quantization, uniform sensitivity quantization, equal area (maximum entropy) quantization, and minimum deviation quantization and the relative merits of the systems were compared and contrasted for fixed and variable rate systems. The principle conclusions of this work were somewhat negative, but not surprising for an information theorist. It was found that when one is constrained to single-symbol quantization, i.e., to separately quantizing individual reflection coefficients and hence be unable to use the correlation among these quantities, then optimal and suboptimal schemes provide nearly the same performance and hence one might as well use the simplest scheme. Thus if one wishes to obtain any real improvement over the LPC systems, it is necessary either to use the correlation of the reflection coefficients within a time frame or sequentially in time. This work was published in [5].

The above research led us to begin to look at ways of more efficiently compressing the reflection coefficients as well as alternatives to the LPC approach. Two possible approaches were suggested by our previous work:

1. Develop a Lloyd-Max style algorithm to optimally quantize the entire vector of 10-12 reflection coefficients for each time frame.
2. Develop a fake process tree code for direct application to the original waveform. These approaches took a long time to implement because of two fundamental problems:
   1. It was not clear what mathematically tractable yet subjectively meaningful distortion measure could be used to define "optimal", and

2. There do not exist good generally accepted probabilistic models for speech and hence techniques like Lloyd-Max which require a model could not be used.

The first problem led to a large literature search and many discussions with people in the speech field. We found useful characterizations of many proposed distortion measures, developed their mathematical properties and their relative strengths and weaknesses, and we summarized our findings in a preliminary Technical Report [6] so as to make this yet unpolished work available to interested people. Our main conclusions were that for several reasons the Itakura-Saito distortion, the log spectral deviation, and the filter distortion were the most promising. On the probabilistic model problem, we developed an algorithm (described in the subsection on Quantization) that will take a quantizer and a data sequence (a training sequence) and will produce a locally optimum quantizer by iteratively improving the partition and the reproduction values that define the quantizer. An initial quantizer for a vector of reflection coefficients is chosen by a technique resembling a predictive quantizer across the reflection coefficient vector and then the iterative algorithm is applied. The training sequence is simply LPC coded standard speech files. Numerous simulations and the results look good on paper (comparable signal to noise ratios in terms of spectral deviation at half the usual LPC rate), but we are awaiting digital-to-analog conversion (LPC synthesis) which must be done elsewhere before making any specific claims. This research will be continued under AFOSR Contract #F49620-78-C-0087. We also feel that if this research proves successful, it will provide the needed codebook of elementary

speech sounds to use in a direct tree coding system not involving any on-line LPC analysis.

Optimum Quantization

As an offshoot of the above work on quantization of reflection coefficients a new and simple development of the basic theory of asymptotically optimum quantizers was obtained. In particular, it was shown that the basic properties of asymptotically optimum quantizers follow easily from standard inequalities of information theory (such as Jensen's inequality) and that variational techniques are not required. This work was published in [7].

The classical Lloyd-Max algorithm for determining an optimum quantizer for a specific source and distortion measure requires a probabilistic description of the source. In practical situations, however, this model must be obtained by observing a "training sequence" of data and applying statistical techniques. We developed a simple and convergent algorithm that operates directly on the data without any explicit model construction and produces a locally optimum quantizer in a sample average sense. If the source is ergodic, then our quantizer will converge to the Lloyd-Max quantizer for the "true" underlying probabilistic model in the limit of a long training sequence. Our technique is a simple sequence of optimizing a partition for a set of reproduction values and then optimizing the reproduction values for the given partition. The approach generalizes a straightforward fashion to optimum vector quantization and its application to speech compression was described above. This work has been written up and submitted for publication [8].

REFERENCES

1. R.M. Gray, "Time-Invariant Trellis Encoding of Ergodic Discrete-Time Sources with a Fidelity Criterion," IEEE Trans. on Infor. Theory, IT-23, pp. 71-83, Jan. 1977.

2. R.M. Gray, "Block, Sliding-Block, and Trellis Source Coding," contributed chapter in Topics in Information Theory, I. Csiszar and P. Elias, Editors, North-Holland, New York, 1977.

3. Y. Linde and R.M. Gray, "A Fake Process Approach to Data Compression," IEEE Trans. Comm., July 1978.

4. Y. Linde and R.M. Gray, "The Design of Tree and Trellis Data Compression Systems," ISL Technical Report 6504-2, Stanford University, February 1978.

5. A.H. Gray, Jr., R.M. Gray, and J.D. Markel, "Comparison of Optimal Quantizations of Speech Reflection Coefficients," IEEE Trans, on Acoustics, Speech, and Signal Processing, ASSP-25, pp. 9-23, Feb. 1977.

6. Y. Matsuyama, A. Buzo, and R.M. Gray, "Spectral Distrotion Measures for Speech Comparison," ISL Technical Report 6504-3, Stanford University, April 1978.

7. R.M. Gray and A.H. Gray, Jr., "Asymptotically Optimal Quantizers," IEEE Trans. on Info. Theory, IT-23, pp. 143-144, Feb. 1977.

8. Y. Linde and R.M. Gray, "Optimum Quantization for Sources Without a Statistical Model," preprint.

SECTION II - D

PROOF OF OPTIMALITY OF TREE CODES

The convolutional source encoding technique described earlier in the section used a convolutional code at a rate $R > 1$ for obtaining compression. Previously, Goblick had suggested the use of normal convolutional codes with $R < 1$ for source coding. In order to obtain compression, he reversed the roles of the encoder and decoder. Jelinek gave a proof of the optimality of such codes, but we found an error in this proof which invalidates it for all but symmetric sources. Utilizing recent results from the theory of branching processes with random environments we re-established the theorem for the entire class of discrete memoryless sources. The new proof also indicates that certain changes in the encoding algorithm are necessary if the complexity is to remain within reason. A paper, "On Tree Coding With a Fidelity Criterion," has been published in the IEEE Transactions on Information Theory (July 1975).

SECTION II - C

MULTIUSER COMMUNICATIONS

Until recently, most coding techniques were designed for point-to-point communication over a single transmission link. Recently it has been found that optimizing the coding for an entire communication network, with more than one transmitter-receiver pair, can yield superior performance to that obtainable by optimizing each link separately. Initially, all of these analyses were either of the broadcast channel with one transmitter and several receivers, or of the multi-access channel with several transmitters and one receiver. We obtained some of the first results for multiuser networks with more than one transmitter and more than one receiver. The network studied was the simplest of this type, with two transmitters and two receivers, and with additive Gaussian noise. We found lower bounds on the capacity region for this channel which we believe to be tight. However, we have not been able to obtain comparable upper bounds. The few upper bounds we have are quite loose over most of their range. Even so, we have been able to establish several interesting properties of this multiuser system. Consider the situation in which transmitter 1 wishes to communicate with receiver 1, and transmitter 2 wishes to communicate with receiver 2, but there is interference between their signals. In the case of symmetrical interference we have

$$r_1(t) = s_1(t) + \sqrt{\alpha}\, s_2(t) + n_1(t)$$

$$r_2(t) = s_2(t) + \sqrt{\alpha}\, s_1(t) + n_2(t)$$

where $r_i(t)$ is the received waveform at receiver i, $s_i(t)$ is the waveform transmitted by transmitter i, α is the interference coefficient (in power), and $n_i(t)$ is white Gaussian noise introduced at receiver i. We further symmetrize the problem by restricting each transmitted signal to have power P, and by making both noises of the same spectral height $N_0/2$. If $\alpha = 0$ there is no interference, and each transmitter can send at full capacity

$$C = W \log_2(1 + (P/N_0W)) \text{ bps}$$

where W is the available bandwidth. As α is increased it is not possible for both transmitters to operate at capacity. Time division use of the band would allow each transmitter to send at C/2 under a peak power constraint. Frequency division would perform somewhat better, but still well below C for usual values of SNR.

Surprisingly, if α is large enough and each transmitter uses all of the bandwidth all of the time, it is possible for each to transmit at rate C reliably. Receiver i first detects signal $\sqrt{\alpha}\, s_j(t)$, $j \neq i$. Since $\alpha >> 1$ it can do this reliably even in the presence of noise $n_i(t)$ and "interference" $s_i(t)$, which is really the desired signal. Once $\sqrt{\alpha}\, s_j(t)$ is known, it is subtracted from $r_i(t)$ to obtain $s_i(t) + n_i(t)$, which corresponds to no interference and therefore allows full capacity to be used!

The above argument is somewhat limited in direct practical value since α is not usually known. However, there are techniques, such as noise cancelling, which work well when there is strong interference and the above argument adds to their theoretical basis.

A paper on this topic, "A Case Where Interference Does Not Reduce Capacity", has appeared in the IEEE Transactions on Information Theory (Sept. 1975).

Another contribution in the multiuser area is a paper, "On Wyner's wiretap channel," which appeared in the IEEE Transactions on Information Theory (May 1977). This paper shows that it is possible for the legitimate transmitter and receiver to communicate at full capacity and to keep the "wire tapper" completely ignorant of a large portion of the message. This is an improvement over the previously known results which required a loss of capacity to achieve complete secrecy.

We also showed that feedback can be used to advantage on both wire-tap and multiple access channels.

Also in the area of multiuser communication systems, a paper, "Bistable Behavior of ALOHA-Type Systems," appeared in the IEEE Transactions on Communications (April 1975). This paper describes a potential instability in packetized radio networks and suggests mehtods to remove the instability. ARPA is currently testing the packet radio concept for military use, and preliminary indications are that it is attractive for many applications. The importance of avoiding instabilities is increased because they tend to occur just when the system is most needed (i.e., when traffic increases).

SECTION III - A

PUBLICATIONS SUPPORTED UNDER CONTRACT #F-44620-73-C-0065

1. A.B. Carleial and M.E. Hellman, "Bistable Behavior of ALOHA-Type Systems," IEEE Trans. on Comm., Vol. COM-23, April 1975, pp. 401-410.

2. C.R. Davis and M.E. Hellman, "On Tree Coding with a Fidelity Criterion," IEEE Trans. on Info. Theory, Vol. IT-21, July 1975, pp. 373-378.

3. M.E. Hellman, "Convolutional Source Encoding," IEEE Trans. on Info. Theory, Vol. IT-21, Nov. 1975, pp. 651-656.

4. R.M. Gray, "Time-Invariant Trellis Encoding of Ergodic Discrete-Time Sources with a Fidelity Criterion," IEEE Trans. on Info. Theory, IT-23, pp. 71-83, Jan. 1977.

5. A.B. Carleial and M.E. Hellman, "A Note on Wyner's Wiretap Channel," IEEE Trans. on Info. Theory, Vol. IT-23, May 1977, pp. 387-390. (Correspondence)

6. R.M. Gray, "Block, Sliding-Block, and Trellis Source Coding," contributed chapter in Topics in Information Theory, I. Csiszar and P. Elias, Editors, North-Holland, New York, 1977.

7. A.H. Gray, Jr., R.M. Gray, and J.D. Markel, "Comparison of Optimal Quantizations of Speech Reflection Co-efficients," IEEE Trans. on Acoustics, Speech, and Signal Processing, ASSP-25, pp. 9-23, Feb. 1977.

8. R.M. Gray and A.H. Gray, Jr., "Asymptotically Optimal Quantizers," IEEE Trans. on Info. Theory, IT-23, pp. 143-144, Feb. 1977.

9. Y. Linde and R.M. Gray, "The Design of Tree and Trellis Data Compression Systems," ISL Technical Report 6504-2, Stanford University, February 1978.

10. Y. Matsuyama, A. Buzo, and R.M. Gray, "Spectral Distortion Measures for Speech Compression," ISL Technical Report 6504-3, Stanford University, April 1978.

11. Y. Linde and R.M. Gray," A Fake Process Approach to Data Compression," IEEE Trans. Comm., July 1978.

12. S.K. Leung-Yan-Cheong and M.E. Hellman, "The Gaussian Wire-Tap Channel", to appear IEEE Trans. on Info. Theory.

13. E. Verriest and M. Hellman, "Convolutional Encoding for Wyner's Wiretap Channel" to appear IEEE Trans. on Info. Theory.

14. Y. Linde and R.M. Gray, "Optimum Quantization for Sources Without a Statistical Model," preprint.

SECTION III - B

Ph.D THESIS SUPPORTED UNDER CONTRACT F44620-73-C-0065

Charles Davis, "Tree Codes and Branching Processes", May 1975.

Aydano Carlieial, "On the Capacity of Multiple-Terminal Communication Networks", August 1975.

S.K. Leung-Yan-Cheong, "Multi-User and Wiretap Channels Including Feedback", July 1976.

Yoseph Linde, "The Design of Tree and Trellis Data Compression Systems", December 1977.